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A Truthful Auction Mechanism for Mobile Crowd Sensing With Budget Constraint

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ABSTRACT The selfishness and randomness of users in the mobile crowd sensing network could cause them unwilling to participate in sensing activities and lead to lower completion rates of sensing tasks. In order to deal with these problems, this paper proposes a novel incentive mechanism based on a new auction model for mobile crowd sensing, which consists of two consecutive stages. In the first stage, a novel Incentive Method based on Reverse Auction for Location-aware sensing (IMRAL) is proposed to maximize user utility. By introducing a task-centric method to determine the winning bids, it can provide higher user utility and higher task coverage ratio. To ensure the truthfulness of IMRAL, we design a unique payment determination algorithm based on critical payment for the incentive platform. In the second stage, we propose a user-interaction incentive model (UIBIM) to cover the situation that a user may drop out of the sensing activity. This new incentive model includes a dynamic double auction framework prompting users' interaction and a user matching algorithm based on a bipartite graph. The proposed new mechanism achieves the goal of improving task completion rates without increasing the cost of the incentive platform. The simulation results show that comparing with other solutions, such as a truthful auction for location-aware collaborative sensing in mobile crowdsourcing and incentive mechanism for crowdsourcing in the single-requester single-bid-model, IMRAL can achieve better performance in terms of average user utility and tasks coverage ratio, and the UIBIM can significantly improve task completion rates.

INDEX TERMS Mobile crowd sensing, incentive mechanism, task coverage, double auction.

I. INTRODUCTION

With the rapid development of wireless communication and sensor technology and the rapid spread of smart terminals, smartphones and tablets have integrated powerful computing and sensing modules such as GPS, accelerometers, gyroscopes, microphones, and cameras. These technologies allow people to perceive and obtain information about their surroundings at anytime, anywhere. A large number of mobile crowd sensing (MCS) systems [1] based on sensing information are also emerging. Typical examples include BlueAer [2] for providing a fine-grained 3D PM 2.5 concentration distribution, Ear-Phone [3] for creating noise maps, and VTrack [4] for providing traffic information. All these applications are MCS systems that perform data collection tasks by a large number of participants.

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In MCS applications, it is necessary to attract more users to participate in the sensing tasks to collect the required data of MCS applications. Therefore, whether there are adequate users taking part in the sensing tasks has a critical impact on the quality of services of such systems. However, in reality, there are several problems that may hinder users' participation. First, the usage of smartphone sensors brings human concerns on privacy. Second, it may increase cost to the participants in transmitting the sensing data to the MCS server. Finally, the consumption of computation/energy resources could also affect users' willingness to contribute their data. To overcome these problems, incentive mechanisms are crucial to stimulate users to join in MCS sensing activities [5]. Normally, the incentive mechanisms can be divided into three categories: incentive mechanisms based on entertainment [6], [7], reputation credit [8], [9], and money. For these three types of incentives, Reddy *et al.* [10] pointed out that the effect of incentive mechanisms based on money is better. The money reward methods are mainly based on the game theory, among which the most important is auction mechanism, such as reverse auction, combined auction, multi-attribute auction. In general, designing a reasonable incentive mechanism based on auction model should consider four characteristics including individual rationality, truthfulness, social welfare, and computation efficiency. In short, the main work of an incentive mechanism should focus on how to encourage participants with money or entertainment rewards, encouraging them to join the sensing tasks.

However, due to the selfishness and uncertainty of a participant's activity, the design of the incentive mechanism of MCS based on the auction model is highly complicated. The selfishness lies in the fact that users' smart terminals are limited by various resources such as the processing power of the device, storage space and battery energy, which makes them generally unwilling to participate in the sensing activities without compensation. In the incentive mechanism, crowd sensing encourages users to participate in sensing tasks by paying a certain amount of money to users. However, in the current incentive mechanism [11]–[18], more consideration is focused on maximizing the benefit of the crowd sensing platform, and the benefit of the participants are not prioritized, which makes the participants cannot be effectively motivated to join in the sensing tasks. From the perspective of a user, the incentive mechanism designed to maximize a user's utility may play a more efficient role.

The uncertainty lies in the fact that, a participant may drop out of an on-going sensing task because of the random movement or some emergency situation, which may make the task to be unfinished. The works presented in [15]–[19] assumes that the users selected to perform the sensing task can complete the sensing task, that is, the task coverage is the same as the task completion. However, in the case of users' random exit during the sensing process, most of the incentives are work in a preventive manner, that is to encourage users stay in the system as long as possible, and they do not consider how to deal with the situation after users exiting. The situation in which a user randomly exits during the sensing process is ignored.

In order to solve the above problems, this paper proposes an incentive mechanism of MCS network based on auction model to divide the users' incentive mechanism into two stages. In the first stage, in order to ensure the truthfulness of the incentive mechanism, and to make participants stay in the system as long as possible, we proposed an incentive method based on reverse auction. This method maximizes users' utility on the premise that the platform budget is feasible, and improves the sensing enthusiasm of user and task coverage. Furthermore, considering the issue of lower task completion rate that is caused by the users' uncertainty, we propose an incentive model based on users' Bidirectional interaction. The model improves the task completion rate without increasing the budget cost of the platform by allow the drop-out participants in stage 1 can resell their sensing tasks to new users according to the double interaction incentive mechanism in stage 2, which can improve the task completion rate as possible without increasing budget of sensing platform. Specifically, the main contributions are summarized as follows:

1. In the stage 1, we design a novel incentive mechanism named IMRAL (incentive method based on reverse auction for location-aware sensing) based on reverse auction to encourage users to participate in sensing activities. In the IMRAL, we prove that the winner selection under certain coverage conditions in NP problem, and proposes a task-centric winner selection algorithm to improve user utility and task coverage. The computational complexity of the algorithm is polynomial time. Furthermore, in the compensation payment stage, we adopt a compensation-based payment algorithm based on the critical price. According to the task performed by the user, the user is rewarded with a time-shared rule to improve the user's utility.

2. In order to cope with the situation that the crowd sensing platform needs to recruit users due to the user quit in the middle of the sensing task, we propose a new incentive mechanism UIBIM (user interaction incentive model) based on user interaction model, which allows the drop-out users to resell their sensing tasks to new users In UIBIM, we design a dynamic double auction mechanism, and for the user matching problem in a single time period, we propose a user matching algorithm based on bipartite graph, which achieves the goal of improving the task completion rate without increasing the platform cost.

3. We compare and analyze the IMRAL mechanism proposed in the first stage and the TRAC mechanism in [13] and the IMC-SS in [18] in terms of user average utility, platform utility, task coverage and task completion rate. Furthermore, we use the task completion rate and platform cost to analyze the effectiveness of UIBIM. The experimental results show that the incentive method IMRAL proposed in the first stage can effectively improve the task coverage and the enthusiasm of users to participate in sensing, and the incentive method based on user interaction that proposed in the second stage can effectively improve the completion rate of sensing tasks. If your paper is intended for a conference, please contact your conference editor concerning acceptable word processor formats for your particular conference.

II. RELATED WORK

Incentive mechanism for mobile crowd sensing mainly include three types, which are entertainment games, reputation values and compensation payments. Entertainment means that sensing tasks are turned into playable games to attract participants. For example, in order to establish a WiFi coverage map in a certain area, the paper [7] designed an outdoor game called Treasure, in which game players carry mobile devices equipped with GPS and WiFi to participate in the game. In this game, the game player needs to pick up the virtual coins scattered on the game area, then upload the coins to the server to obtain the game points. The better network connection the more possibility of collecting and uploading coins successfully. In this way, the player is encouraged to find a place with a strong WiFi coverage signal, and a WiFi coverage map of an area is established and updated by the player's mobility. The incentive methods based on the reputation values refer to the user obtaining a certain reputation value by performing the sensing task, such as satisfaction, social status and etc. On the other hand, the platform can also select users of high quality to perform sensing tasks based on the user's reputation value. In order to solve the problem of network performance degradation caused by the unwillingness of selfish nodes in the opportunity network to forward messages, Bigwood and Henderson [9] have proposed an incentive mechanism for opportunistic networks named IRONMAN (incentives and reputation for opportunistic networks using social networks) to encourage users to participate in message forwarding to improve network performance. The incentive method based on compensation payment refers to using money to compensate the sensing cost of a user to motivate the user to participate in the sensing. Reddy *et al.* [10] pointed out that the incentive effect of the incentive method using compensation payment is often more effective than the non-monetary incentive method.

In order to stimulate user's participation, in [14], a profit maximizing auction mechanism has been proposed. The goal of the mechanism is to maximize the profit of the platform, while motivating smartphone users to participate in auctions at real cost to ensure the truthfulness of the incentives. In [20], in order to encourage users to participate in sensing and maximize the benefits of the platform, an auction mechanism is proposed to motivate users to participate. In this mechanism, the platform only pays for the most contributing users, not all participants, and the compensation is not a fixed value, but a function of the maximum contribution of all participants. Zhao *et al.* [21] have considered the scenario in which a user submitted the bid to the platform at the time of arrival, and maximized the utility of the platform under budget constraints by selecting an appropriate subset of users in each time period. In [22], in order to encourage users to complete a set of binary marking work under certain budget conditions, they cluster the markers collected by continuous Bayesian method and design an incentive mechanism based on the reverse auction model. The sensing platform selects a winner according to the difficulty level of a task and the completion quality of the worker, and pays the user according to the aggregated user bidding. Thus, the final platform can achieve a higher utility within a certain budget. Luo *et al.* [23] have presented an auction mechanism for multiple cooperative tasks to minimize the server's payment under the condition that the server earns the targeted value. However, most of the above research work is aimed at maximizing platform utility. The user's utility is not fully considered, resulting the enthusiasm of users to participate in sensing is low.

In response to the user's random exit, Jaimes *et al.* [16] designed an incentive mechanism based on multiple rounds of reverse bidding to encourage users to participate in sensing plans that require continuous and periodic sampling. The mechanism not only considers the user's bid and also considers the user's location when selecting a user. The experimental results show that the mechanism can achieve an optimal budget utilization while ensuring that the sensing area is covered and that there are enough users for each round of auction. In [24], it is pointed that in participatory sensing, it is crucial to motivate users to engage in sensing activities for a long time. In order to motivate users to participate in sensing activities for a long time, they design an incentive mechanism based on VCG (Vickrey clarke groves) auction model and use this mechanism to select users online. The mechanism pays the participants' compensation according to the time period, and realizes the long-term incentive. In [17] , in order to minimize the platform payment while ensuring a high participation rate, Lee and Hoh used the reverse auction mechanism to select the lowest bidder among the participants as a winner. They introduced the concept of virtual participation points to avoid the situation that a participant would exit the auction if he/she is repeatedly failed in the previous auction rounds. Depending on the different number of requesters and providers, Zhang *et al.* [18] have considered three different models: SS-Model (Single requester, Single bid), SM-Model (Single requester, Multiple bid) and MM-Model (Multiple requester, Multiple bid). However, they fail to consider that the winners may exit during the sensing process. Among them, SM-Model is the general form of SS-Model, and MM-Model considers two kinds of competition modes: competition between multiple groups of crowd sensing platforms and competition among multiple users. However, most of the above studies assume that the user who wins the task will be able to complete the task and upload the data. It does not consider that a winner may exit the sensing task under a random probability during the execution of the task. This situation causes the sensing task to be interrupted and the task completion rate to decrease. In the above case, if the platform recruits a new participant to continue the unfinished sensing task, it is necessary to pay the newly recruited users, which ultimately leads to an increase in the sensing cost of the platform.

III. PROBLEM DEFINITION

A. RELATED DEFINITION

The framework of our proposed incentive mechanism is shown in Fig.1. In the first stage, we aim to improve the user utility and task coverage through the reverse auction incentive model. In IMRAL, we leverage the task-centric algorithm to select winner in our auction model, and pay winners based on critical price to make them stay in the system as long as possible. Considering there may be some participants exiting the sensing tasks, which will make their sensing tasks unfinished, causing a low task completion ratio. If the platform to recruit new users, the budget will be increased. In this case, we propose to allow these participants to resell their unfinished tasks to new users based on double auction among them. In this model, we construction bipartite graph model to

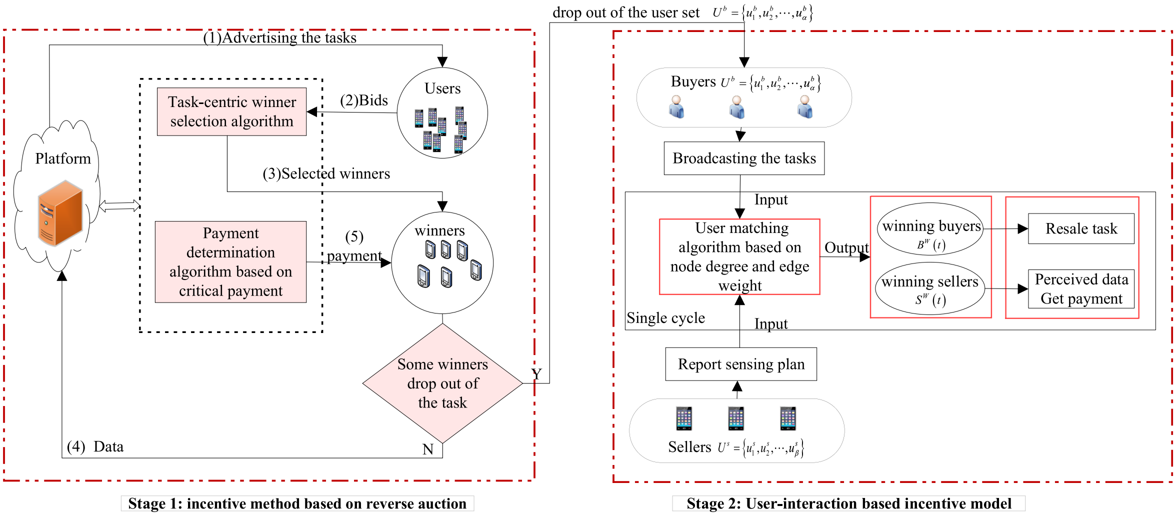

FIGURE 1. **The incentive framework based on auction model.**

match the buyers and sellers in a single time period, and its computational complexity is in polynomial time order. In the crowd sensing system, there is a crowd sensing platform that selects user sets from multiple users to meet the coverage requirements of the sensing tasks. Papers [13] and [18] give the relevant definitions below:

Definition 1: $\Gamma = \{\tau_1, \tau_2, \cdots, \tau_m\}$ is used to denote the sensing tasks' set. For each $\tau_i \in \Gamma$, Let s_i represents the start time to perform the task, d_i is the deadline, before which the sensed data must be submitted, t_i is the time required for a user to complete the task τ_i, and V_i denotes the sensing task values. The sensing task value is a private information of the platform. In addition, we have $d_i - s_i \geq t_i$, which means that the required time to complete the task should not exceed the valid time of the task.

Definition 2: $U = \{u_1, u_2, \cdots, u_n\}$ is used to denote smartphones users which are interested in performing sensing tasks. Each user $u_i \in U$ submits the task-bid pair $B_i = (\Gamma_i, b_i)$ to the platform, in which Γ_i ($\Gamma_i \subseteq \Gamma$) is a subset of sensing tasks that are reported by the user u_i, and b_i is called bid of the subset of task Γ_i which is a reserved price that user u_i wants to sell its service.

Definition 3 (Task Coverage): Let num_i denotes the number of winners for a task τ_i, the task τ_i is covered if and only if $num_i \geq 1$. In addition, $num_i = 1$ denotes that the task τ_i is performed by only one user.

Definition 4 (Sellers): $U^s = \left\{u_1^s, u_2^s, \cdots, u_\beta^s\right\}$ is used to denote sellers in stage 2 in Fig.1, who want to participate in sensing activities.

Definition 5 (Buyers): $U^b = \left\{u_1^b, u_2^b, \cdots, u_\alpha^b\right\}$ is used to denote buyers in stage 2 in Fig.1, who drop out of a sensing task in stage 1.

The description of some symbols is shown in Table 1.

TABLE 1. **Description of some symbols.**

Symbol	Descriptions
U,n,u_i	The set of users, the total number of users, and a user in U.
Γ,m,τ_i	The set of sensing tasks, and the total number of tasks, a task in Γ.
s_i,d_i	the start time to perform the task τ_i, and the deadline of the task τ_i.
t_i,Δt_i	The time to complete the sensing task by users,and the time to perform the task τ_i by user u_i.
V_i	The task value of task τ_i.
Γ_i,v_i	The total sensing task values in Γ_i.
b_i	The bid of the user u_i.
c_i	The sensing costs of the user u_i.
p_i	The payment of the user u_i.
S	The set of winners.
T_{τ_i}	Task rewards.
$U^b\left(u_i^b\right)$,$U^s\left(u_j^s\right)$	The set of buyers (buyer), the set of sellers (seller).
$B(t)\,(S(t))$	The set of buyers or the set of sellers who arrive in period t.
$B^W(t)$	The set of winning buyers in time t.
$S^W(t)$	The set of winning sellers in time t.
$\lvert B(t)\rvert\,(\lvert S(t)\rvert)$	Number of the users in $B(t)$ or $S(t)$.

B. AUCTION MODEL

1) INCENTIVE METHOD BASED ON REVERSE AUCTION

As shown in Fig. 1, in the first stage, in order to improve the enthusiasm of a user's participation in sensing tasks, and considering the situation where the user may randomly exit the sensing activities, we present an incentive method based on reverse auction model to motivate users to participate. The interaction process between the platform and users is shown in Fig. 2, the concrete steps are as follows:

1. The platform advertises the description of a sensing tasks' set $\Gamma = \{\tau_1, \tau_2, \cdots \tau_m\}$, each task $\tau_i \in \Gamma$ has its

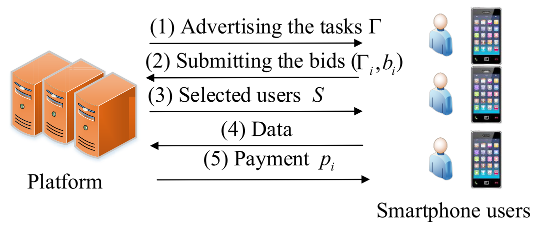

FIGURE 2. **The interaction between the platform and smartphone users.**

corresponding attributes, including the task start time s_i, he task deadline time d_i, the time t_i required by the user to complete the sensing task τ_i, and the value V_i of the task τ_i. The time period from a task's start time s_i to a task's deadline d_i is the valid time of task, and the value is not less than the time t_i, that is, $d_i - s_i \geq t_i$. The sensing task value $V = \{V_1, V_2, \cdots, V_m\}$ is the private information of the platform, and the sensing tasks are related to the location, that is, each task needs to be completed at a specific location.

2. Let $U = \{u_1, u_2, \cdots, u_n\}$ be a user set, and a user can decide whether or not to participate in a sensing task, which we represent them as dormancy or bidding situations respectively. For convenience, we consider a user as dormancy situation when the user is unwilling to participate in a sensing task. Therefore, we introduce the sensing task 0. When a user is in dormancy situation, it means that the user selects the sensing task 0, and the corresponding utility of that user is 0. User u_i who made the bid submits the task bid pair $B_i = (\Gamma_i, b_i)$ according to his or her location. $\Gamma_i (\Gamma_i \subseteq \Gamma)$ is the subset of tasks reported by a user, and b_i is the bid for a user to report the subset of the task, that is the price that user u_i is willing to provide the data service.

3. According to the task bid pair $B = \cup_{u_i \in U} B_i$ submitted by all users, the crowd sensing platform selects the user subset $S \subseteq U$ as the winner of the task to satisfy the sensing task coverage requirement.

4. Each winner performs the sensing tasks in its winning bids and sends the sensing data back to the platform.

5. According to whether a winner u_i has completed task τ_i or not, each winner u_i is paid an amount of money p_i for its winning bid b_i.

a: USER NODE UTILITY MODELING

The cost of a user's participation in a task is determined by factors such as energy loss caused by the provision of services, network bandwidth resource consumption, and potential privacy threats. The cost of user u_i participating in a sensing task is $c_i\,(0 < c_i \leq b_i)$, which is the private information of that user.

The utility of user u_i is the difference between the money p_i obtained by participating in the sensing task and its sensing cost c_i, which is defined as follows.

$$\tilde{u}_i = \begin{cases} p_i - c_i, & if\, u_i \in S \\ 0, & otherwise \end{cases} \tag{1}$$

b: CROWD SENSING PLATFORM UTILITY MODELING

The utility of the crowd sensing platform is the difference between the total value $v(S)$ of the tasks completed by all the winners and the total compensation payments to all the winners. The definition is as follows.

$$u_0 = v(S) - \sum_{u_i \in S} p_i \tag{2}$$

2) USER-INTERACTION BASED INCENTIVE MODEL

As shown in Fig. 1, in the second stage, some selected users may drop out of a sensing task randomly, which results in low task completion ratio. When the random dropping happens, more users need to be recruited for the uncompleted sensing tasks to maintain the task completion rate and the service quality for MCS applications, which could increase the cost of the MCS platform and data redundancy.

In order to improve the task completion rate without increasing the budget cost of the platform, this paper establishes the interaction model between users to motivate users to conduct transactions and prompt the task to be completed. The specific interaction process is shown in Fig. 3. There are three interactive entities in this model, buyers $u^b = \{u_1^b, u_2^b, \cdots, u_\alpha^b\}$ that are composed of buyer $u_i^b \in u^b$, sellers $u^s = \{u_1^s, u_2^s, \cdots, u_\beta^s\}$ that are made up of seller $u_j^s \in u^s$, and crowd sensing platform. The interaction process of the interaction entity is as follows. First, the seller $u_j^s \in u^s$ broadcasts the task requirements. After knowing the specific requirements of the task, the buyer $u_i^b \in u^b$ submits a sensing task. As the seller and user randomly arrives and leaves, a dynamic system is formed. Then, we design a user matching strategy to determine winning buyers and winning sellers. The winning buyers will recommend the winning sellers to the platform, and after the sellers complete the sensing task and upload the sensing data to the platform, the platform pays the buyers. Finally, the winning buyers pays the compensation p_i to the winning sellers.

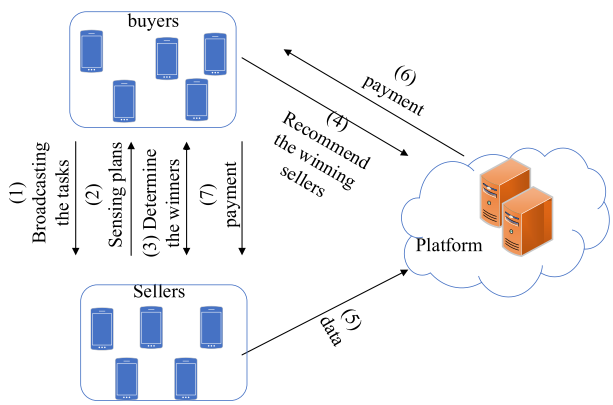

FIGURE 3. **User-interaction model.**

Assuming that the total time period for user transactions is T, and $t = 1, 2, 3 \cdots, T$. Each user has its own specific type of sensing $\theta_i = (a_i, d_i, w_i)$, a_i and a_i are arrives time and leaves time of a user respectively, and assuming that a user's maximum arrival-departure interval is I, which is called maximum waiting patience. For a buyer, $w_i = b_i$ is buyer's bid, indicating that the buyer $u_i^b \in u^b$ does not purchase the sensing data higher than this price. For a seller, $w_j = s_j$ is the asking price, indicating that the seller sells the sensing data no less than the asking price. Therefore, the buyer's utility can be expressed as $u\left(u_i^b\right) = b_i - p_i$ and the seller's utility can be expressed as $u\left(u_j^s\right) = p_j - s_j$.

C. PROBLEM FORMULATION

1) REVERSE AUCTION BASED INCENTIVE METHOD

In the first stage, this paper considers designing an incentive mechanism with the goal of maximizing a user's utility on the constraint of limited budget of a sensing platform. The formalized representation of this problem is as follows.

$$Maximize \sum_{u_i \in S} p_i - \sum_{u_i \in S} c_i \quad s.t. \sum_{u_i \in S} p_i \leq B \tag{3}$$

where B represents the payment budget of the platform, assuming that its task budget B is not greater than the total value $v(S)$ of all tasks completed by the winners.

As can be seen from the above, there are two problems that need to be solved in the reverse auction incentive method: (1) determine the successful auction users, who can maximize the task coverage while minimizing social costs; (2) design a reasonable payment method to encourage users to bid truthfully, and to encourage them stay in the system as possible as they finish their sensing task.

a: WINNER SELECTION PROBLEM(WSP)

Given a set of users $U = \{u_1, u_2, \cdots, u_n\}$, the platform selects a subset of users $S(S \subseteq U)$ as winners to minimize the sum cost of users and cover all the sensing tasks.

$$\min \sum_{u_i \in S} c_i \quad s.t. \bigcup_{u_i \in S} \Gamma_i = \Gamma \tag{4}$$

Theorem 1: The winner selection problem (WSP) is NP hard.

Proof: In order to prove that this problem is NP-hard, the concept of weighted multiple set cover problem (WMSCP) is introduced first. This problem has been proved to be NP-hard problem by Yang and Leung [25].

An Instance of WMSCP: There are n subsets $\{Y_1, Y_2, \cdots, Y_n\}$ of the base elements set $E = \{e_1, e_2, \cdots, e_m\}$, and a positive integer k as well as a positive-integer-valued m-tuple $(w_1, w_2, \cdots, w_m)$.The question is whether exists a subset $e_i(e_i \subseteq E)$ of size k, such that every element e_i is covered for at least w_i times.

Next, we change the instance of WMSCP to an instance of our problem. Let Γ be the set mapping to E, where there is a task $\tau_i \in \Gamma$ for each $e_j \in E$. Corresponding to each subset $Y_i \in Y$, user $u_i \in Y$ can do the task set Γ_i, which contains tasks mapping to the elements in Y_i. If every element e_i is covered for w_i times, the mapping tasks τ_j is done by multiple users with the size of w_j. This shows that the WMSCP can be reduced to the WSP in a linear time. So, the winner selection problem is NP-hard.

b: PAYMENT DETERMINATION PROBLEM (PDP)

Consider how to ensure the truthfulness of the incentive method when the user exits the sensing task with random probability. Myerson [26] proved that if an auction mechanism is true, it must satisfy two conditions, that is, the selection rule is monotonous and the winner's reward value is a critical price. Monotonicity means that if a user becomes a winner with the bid b_j, then the bid $b_j' < b_j$ can still be the winner. The critical price means that if the bid price b_j of a user is higher than the critical price p_j, the user will not be the winner.

Namely, for each user u_i, let $B_i = (\Gamma_i, b_i)$ denote the truthful bid, and $B_i{}' = \left(\Gamma_i, b_i{}'\right)$ denote the untruthful bid. The payoffs of the user u_i for the truthful bid and the untruthful bid are $u_i(B_i)$ and $u_i\left(B_i{}'\right)$, respectively. Therefore, the PDP problem is to design a payment scheme that satisfies the following conditions:

$$u_i\left(B_i\right) \geq u_i\left(B_i'\right) \tag{5}$$

2) USER-INTERACTION BASED INCENTIVE MODEL

In the second stage in Fig. 1, for the case that a selected user drops out of a sensing task, we propose a user-interaction based incentive model to improve the task completion ratio without increasing the cost of the platform. In this model, the user (namely buyer) who drops out of a sensing task in the first stage can resell the unfinished task to a new user (namely seller) through double auction, which can improve the task completion rate without increasing the platform budget cost.

The process focuses on designing a reasonable double auction mechanism while solving the user matching problem in a single time period. Therefore, an auction mechanism should be designed to maximize economic efficiency while the design mechanism needs to satisfy the computational efficiency, that is, the result of the user matching can be output in the polynomial time.

a: SINGLE TIME PERIOD USER MATCHING PROBLEM

Since the design of the incentive mechanism needs to meet the conditions of computational efficiency, the matching result in a single time period should be output in the polynomial time. In a single time period t, the purpose is to match buyers and sellers with the goal of maximizing the task completion rate. We express the purpose as follows.

$$Max\ (\sum_{u_i^b \in G} y_i) \tag{6}$$

$$s.t.\ x_{ij} \in \{0, 1\} \quad \forall u_i^b,\ u_j^s \tag{7}$$

$$0 \leq \sum\nolimits_{i:(u_i^b, u_j^s) \in G} x_{ij} \leq 1, \quad \forall u_i^b \tag{8}$$

$$0 \leq \sum\nolimits_{j:(u_i^b, u_j^s) \in G} x_{ij} \leq 1, \quad \forall u_j^s \tag{9}$$

$$y_i = \begin{cases} 1, & \forall u_i^b, \quad u_j^s x_{ij} = 1 \\ 0, & otherwise \end{cases} \tag{10}$$

$$G = \{(u_i^b, u_j^s) : a_i \leq d_j, a_j \leq d_i, \\ \exists t, s.t. u_i^b \in B(t), u_j^s \in S(t)\} \tag{11}$$

Equation (6) indicates that the goal of the incentive in stage 2 is to complete as many sensing tasks as possible to improve the task completion rate. In equation (7), when $x_{ij} = 1$, it means that the buyer u_i^b and the seller u_j^s are matched well; otherwise, $x_{ij} = 0$. Equation (8) indicates that any one of the buyers can match at most one seller within the period t. Similarly. Equation (9) means that each seller can match at most one buyer within the period t. When y_i is set to 1, it means that task owned by u_i^b is allocated; otherwise $y_i = 0$. Equation (11) indicates that in any period t, in order to ensure the validity of the match between the buyer u_i^b and the seller u_j^s, it is necessary to ensure that the arrival time of u_i^b is earlier than the departure time of u_j^s, and the arrival time of u_j^s is earlier than the departure time of u_i^b. $B(t)$ and $S(t)$ denote the set of buyers and the set of sellers who arrive in period t respectively.

We consider a multi-user matching problem as a one-to-one matching problem of bipartite graph (V, E), where V denotes the buyers and sellers, and an edge exists between a buyer and a seller if and only if a seller has bid on the tasks held by a buyer. The user matching problem can be better described by the integer programming method. Due to the constraints of constraints (8), (9), and (10), (6) can be simplified to the 0-1 programming problem. The 0-1 programming problem has been proved to be NP-hard [27]. Therefore, the user matching problem is NP-hard.

IV. IMRAL

In this section, to improve the willingness of a user to participate in a sensing task, and deal with the case that a winner may exit randomly during a sensing task, we present a reverse auction based incentive mechanism for location-aware sensing in MCS(IMRAL). The IMRAL consists of two parts: winner selection and payment scheme.

A. THE TASK-CENTRIC WINNER SELECTION ALGORITHM

Theorem 1 illustrates that it is very difficult to solve the winner selection problem. Therefore, it is reasonable to find a solution with lower computational complexity, which has practical significance. Reference [28] demonstrates that, when the number of users participating in a same sensing task increases, diminishing marginal effect caused by data redundancy becomes more serious. For example, when multiple mobile phones simultaneously collect data about the noise level in an area, one or two mobile phones is sufficient to collect the data to estimate the noise level in the area. In contrast, allowing more mobile phones to collect data will not improve the accuracy efficiently, but will increase data redundancy and social costs.

Algorithm 1 Task-Centric Winner Selection Algorithm

Input: set $\Gamma = \{\tau_1, \tau_2, \cdots, \tau_m\}$ of sensing tasks, set $V = \{V_1, V_2, \cdots, V_m\}$ of sensing tasks, set $B = \cup_{u_i \in U} B_i$ of all submitted bids.
Output: set S of winning bids, the tasks set Γ'' covered by all winners, b_1/v_1 and b_L/v_L for $\tau_i \in \Gamma''$.
Initialization: $S \leftarrow \phi$, $\Gamma'' \leftarrow \phi$;
According to $B_i = (\Gamma_i, b_i)$, compute the tasks set $\Gamma' \left(\Gamma' \subseteq \Gamma\right)$ submit by all users, the number of users bid n_i and the bidding users set U_{τ_i};
for all τ_i in Γ' **do**
if $(n_i = 1)$ **then**
if $(b_i \leq v_i)$ **then**
$S = S \cup \{u_i\}$, $\Gamma'' = \Gamma'' \cup \{\tau_i\}$;
end if
end if
if $(n_i \geq 2)$ **then**
Sort b_i/v_i for all $u_i \in U_{\tau_i}$ and the list is denoted by R;
b_1/v_1 denotes the head of R, b_L/v_L denotes the tail of R;
if $b_1/v_1 \leq 1$ **then**
$S = S \cup \{u_1\}$;
$\Gamma'' = \Gamma'' \cup \{\tau_i\}$;
end if
end if
end for
return s, Γ'', b_1/v_1, b_L/v_L

In addition, when the sensing task value is constant, the more users participating in the same task, the less reward each user can receive. This paper considers the marginal diminishing effect of sensing data collection, assuming that each task is performed by one person. In order to improve user utility and task coverage, we propose a task-centric winner selection algorithm in the user selection phase. For each task, the user with the smallest ratio of the bid to the total value of the reported tasks is selected as a winner to perform the sensing task.

The basic idea of the task-centric winner selection algorithm is as follows. Let n_i denotes the number of users bidding for task τ_i. When $n_i = 1$, and $b_i \leq v_i$, where v_i is the sum of tasks value for bid b_i, which means that there is only one user willing to bid for task τ_i and the bidding price b_i is lower than the task value v_i. In this case, we will select that user as the winner to perform task τ_i; when $n_i > 1$, which means there are more than one users willing to perform τ_i, these users are sorted according to the value of b_i/v_i. Which is,

$$b_1/v_1 \leq b_2/v_2 \leq \cdots \leq b_L/v_L \tag{12}$$

if $b_1/v_1 \leq 1$ and b_i/v_i is the smallest, we select the user u_i as a winner for task τ_i. The pseudo-code of task-centric winner selection algorithm is shown in Algorithm 1.

B. COMPENSATION PAYMENT ALGORITHM BASED ON CRITICAL PRICE

After selecting the winner set, the winners perform the task and upload the data according to the tasks they have won. The platform pays for a user according to the user's task completion status. Concerned to the situation that a user may drop out of a sensing task, we have proposed the payment method which considers two situations: a user completes the task normally and a user quits during the sensing process. In order to ensure the truthfulness of the incentives and encourage users to participate for a long time, we use the concept of critical payment in [26] to propose a compensation payment algorithm based on critical price.

We use the time-shared rule to reward a user according to the user bid and the task performed by the user. Specifically, a user's payment function is as follows.

$$p_i = b_i + \sum_{k=1}^{x} T_{\tau_i} \tag{13}$$

where x is the number of tasks wined by user u_i, T_{τ_i} denotes the task rewards for τ_i and is computed as follows:

$$T_{\tau_i} = \begin{cases} V_i\left(b_L/v_L - b_1/v_1\right), & if\ \Delta t_i = t_i \\ V_i(b_L/v_L - b_1/v_1)(\Delta t_i/t_i), & if\ \Delta t_i < t_i \end{cases} \tag{14}$$

where t_i is the time to complete task τ_i, Δt_i denotes the time to perform the task τ_i by user u_i. If the bidder of task τ_i has only user u_i and the bid is successful, when we calculate T_{τ_i}, we use b_i/v_i instead of $b_L/v_L - b_1/v_1$ in (14). When a user performs a certain task, there are only two possible situations, one is that the user completes the task normally, and the other is that the user quits halfway when performing the task. We let p denotes the probability of a winner who completes the task normally, thus $q = 1 - p$ is the probability winner dropping out of a participated sensing task, which follows Bernoulli distribution. That is, $X = 1$ represents that the user completes the task normally when performing a certain task, and the probability is p, and $X = 0$ represents that the user quits halfway when performing a certain task, and the probability is $q = 1 - p$. The pseudo-code of compensation payment algorithm based on critical price is shown as Algorithm 2.

Algorithm 2 Compensation Payment Algorithm Based on Critical Price

Input: set S of winning bids, the task set Γ'' covered by the winner, the minimum value b_1/v_1 and the maximum value b_L/v_L of the ratio of the bid price reported to the user for any task $\tau_i \in \Gamma''$ and the total value of the task report.
Output: critical payment p_i.
Initialization:, $p_i \leftarrow 0$, $\Gamma''' \leftarrow \phi$, Γ''' denote the tasks set completed by all winners;
1: **for all** $\tau_i \in \Gamma''$ **do**
2: Calculate v_i according to function (14);
3: **if** $\Delta t_i = t_i$ **then**
4: $\Gamma''' = \Gamma''' \cup \{\tau_i\}$
5: **end if**
6: Compute $v_{\Gamma'''} = \sum_{\tau_i \in \Gamma'''} V_i$, it represents the total value of the winning set to perform the task;
7: **end for**
8: **for all** $u_i \in S$ **do**
9: Count the tasks that user u_i wins, and the total number x of tasks, Calculate p_i according to function (13);
10: Compute $P = \sum_{u_i \in S} p_i$;
11: **end for**
12: **if** $P > v_{\Gamma'''}$ **then**
13: $S \leftarrow \phi, p_i \leftarrow 0$;
14: **else** $S \leftarrow S, p_i \leftarrow p_i$;
15: **end if**
16: **return** p_i

C. THEORETICAL ANALYSIS

A feasible and effective bidding mechanism needs to satisfy the following characteristics: computational efficiency, individual rationality, budget feasibility, and truthfulness (that is, incentive compatibility) [22]. The first three characteristics are the basic conditions for guaranteeing the viability of the mechanism, and the truthfulness can eliminate the user's concerns about market manipulation. In this subsection, we analyze IMRAL from four aspects: computational efficiency, individual rationality, budget feasibility and incentive compatibility.

Lemma 1: IMRAL is computationally efficient.

Proof: In Algorithm 1, the complexity of the for loop (line 2-16) is $O(m)$, and the computational complexity of the sorting operation (line 9) is $O(nlogn)$. Therefore, the total computational complexity of algorithm 1 is $O(mnlogn)$, that is, the time complexity of Algorithm 1 is in polynomial time order. In Algorithm 2, the complexity of the first for loop (line 1-7) is $O(m)$. The complexity of the second for loop (line 8-12) is $O(n)$. Consequently, the computational complexity of Algorithm 2 is $O(n)$, that is, the time complexity of Algorithm 2 is in polynomial time order. Therefore, the time complexity of IMRAL is in polynomial time order, and IMRAL is computationally efficient.

Lemma 2: IMRAL is individually rational.

Proof: If a user u_i fails to bid, and $p_i = 0, c_i = 0$, then $\widetilde{u}_i = 0$. If a user u_i is successful, and $p_i = b_i + \sum_{k=1}^{x} T_{\tau_i}$, $c_i \leq b_i$, then $\widetilde{u_i} \geq 0$. The user utility is not less than zero, satisfying individual rationality.

Lemma 3: IMRAL is budget feasible.

Proof: Lines 13 to 15 of the compensation payment algorithm guarantees that the task will be started in the case that the compensation is paid should not greater than the total value of the completed tasks. At this time, the platform's utility is greater than or equal to 0, otherwise the task fails to start, and the platform's utility is 0. Therefore, the mechanism is balanced in budget.

Lemma 4: IMRAL is incentive compatible.

Proof: According to [26], it is pointed out that the auction mechanism must satisfy both monotonicity and critical price when it meets the truthfulness. Here, we prove it from monotonicity and critical price.

Monotonicity: Since b_i/v_i is sorted from small to large, assuming that the user u_i becomes a winner in bid b_i. When the user bids with $b_i' \le b_i$, since v_i does not change, user u_i can also be a winner. Critical price: Assume that the number of user participating in the bidding task τ_i is not less than 2, and a user u_i becomes the winner in the bid b_i, then the payment is $p_i = b_i + T_{\tau_i}$. If a user u_i bids with a value greater than b_i, and $b_i > b_i + T_{\tau_i}$, thus $T_{\tau_i} < 0$. Because $T_{\tau_i} = \begin{cases} V_i\left(b_L/v_L - b_1/v_1\right), \text{if } \Delta t_i = t_i \\ V_i\left(b_L/v_L - b_1/v_1\right)\left(\Delta t_i/t_i\right), \text{if } \Delta t_i < t_i \end{cases}$. Then the user u_i will not be able to win the task τ_i. Therefore, if a user uses a value greater than p_i as the bid price, it will not become a winner. Therefore, the mechanism satisfies the incentive compatibility characteristic.

In summary, IMRAL meets computational efficiency, individual rationality, budget feasibility, and incentive compatibility.

V. USER-INTERACTION BASED INCENTIVE MODEL

In order to improve the sensing task completion rate without increasing the platform budget cost, based on the user interaction model, we design a dynamic incentive method based on two-way auction. The method facilitates as many user transactions as possible in a limited period of time to maximize the sensing task completion rate.

A. DYNAMIC DOUBLE AUCTION INCENTIVE METHOD

In order to motivate users to participate and ensure that tasks are completed as many as possible, we propose a dynamic incentive method based on two-way auctions. The incentive execution process of this method is illustrated in Fig. 4. In order to adapt to the situation of the user's dynamic arrival, we divide the incentive method into an auction module and a survivor module. Among them, the main function of the auction module is to make a reasonable match between the buyer and the seller. The main function of the survival module is to make the buyer and seller users have a greater chance of matching successfully in a limited total auction period. The core idea to design the survival module is that if the user does not win in the period $t-1$ and the departure time is greater than $t-1$, then the user can continue to bid in the period t. The dynamic double auction incentive method has two core algorithms: online auction algorithm and user matching algorithm.

The based idea of online auction algorithm is as follows. Assume the total auction period is T, and $t = 1, 2, 3 \cdots, T$, during each period t, the dynamic double auction method first forms a set of buyers $B(t)$ and a set of sellers $S(t)$. In the auction stage, the winning buyers set $B^W(t)$ and the winning sellers set $S^W(t)$ are selected according to a reasonable matching rule. For users who have not entered the winning set and whose departure time d_i is greater than t, they can enter the next cycle as survivors. According to [29], let $SNT_B(t)$ denote a buyer-survivor in the time period t, and $SNT_s(t)$ denote a seller-survivor in the period t. If they are not survivors in the period t, add them to the set $h(t)$.

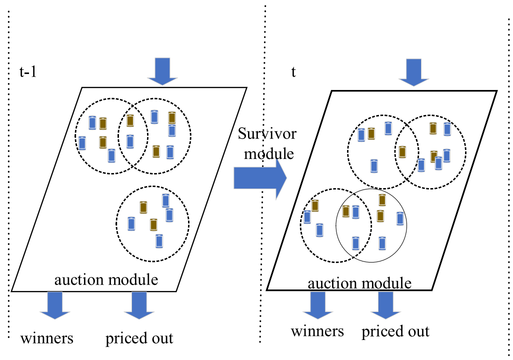

FIGURE 4. The Incentive execution process of dynamic double auction.

B. USER MATCHING ALGORITHM BASED ON NODE DEGREE AND EDGE WEIGHT

In order to ensure a high task completion rate, the buyer nodes are arranged in ascending order of nodes, and the nodes with low degree are matched first. Every edge in the bipartite graph has a positive weight, and it can be computed as $W = b_i - s_j$. In order to maximize social welfare, a user with the largest weight and no less than 0can be a winners. Let $B(t)$ and $S(t)$ denote the set of buyers and seller users arriving in period t respectively.$|B(t)|$ and $|S(t)|$ denote the number of buyers in user set $B(t)$ and the number of seller in user set $S(t)$, where $B^W(t)$ and $S^W(t)$ denote the set of winning buyers and the set of winning sellers in time t respectively. The user matching algorithm based on node degree and edge weight is shown in Algorithm 3.

After the users matched successfully, a reasonable pricing mechanism needs to be designed to motivate users to participate. In order to ensure the truthfulness of the incentive, in the transaction, the transaction price can be calculated as $p_i = p_j = \left(b_i + s_j\right)/2$.

C. ANALYSIS OF DYNAMIC INCENTIVE ALGORITHM

In this subsection, we conduct the theoretical analysis and prove that the dynamic incentive algorithm satisfies the properties of individual rationality, incentive compatibility, and computational efficiency.

Lemma 5: The dynamic incentive algorithm achieves individual rationality.

Proof: For each buyer $u_i^b \in U^b$, if a buyer fails in an auction, then the utility of the buyer will be zero. If he wins, then the utility of the buyer can be calculated as $u\left(u_i^b\right) = b_i - \frac{b_i + s_j}{2} = \frac{b_i - s_j}{2} \ge 0$. Therefore, the utility of buyer $u_i^b \in U^b$ is $u\left(u_i^b\right) \ge 0$. In summary, for any buyer, the dynamic incentive algorithm proposed in this paper is individual rational.

Similarly, we can prove for any seller that the dynamic incentive algorithm is individual rational.

Lemma 6: The dynamic incentive algorithm satisfies the property of incentive compatibility.

Proof: An incentive algorithm is incentive compatible if and only if it meets the following two conditions: (1) The task allocation rule is monotone; (2) Each winner is paid or obtained a critical payment.

We first show that the task allocation rule is monotone. Assuming that there are n ($n \geq 2$) sellers bid for a task which is owned by the buyer u_i^b, and the seller wins the sensing task with u_j^s. If $S_j = \left(a_j, d_j, s_j\right)$ bids with $S_j' = (a_j', d_j', s_j')$, where $a_j \leq a_j' \leq t$, $d_j' \leq d_j$ and $s_j' < s_j$, since b_i does not change, a seller u_j^s can also win a task.Secondly, we show that each winner is paid or obtained a critical price. If the seller u_j^s wins with s_j, its obtain is $p_j = \frac{b_i+s_j}{2}$. If u_j^s bids with $s_j > p_j$, then $s_j > \frac{b_i+s_j}{2}$, and $s_j > b_i$, Thus, u_j^s cannot win. Therefore, each seller gets a critical price. And so on, each buyer pays a critical price.

Lemma 7: The dynamic incentive algorithm is computationally efficient.

The complexity of the sorting operation (line 1) in algorithm 3 is $O(|B(t)|\log|B(t)|)$, the complexity of the for loop (line 2 to line14) is $O(|B(t)||S(t)\log|S(t)|)$. Therefore, the total computational complexity of algorithm 3 is $O(|B(t)||S(t)\log|S(t)|)$. According to the analysis of the time complexity of Algorithm 3, the time complexity of the online auction algorithm is $O(T|B(t)|(|B(t)| + |S(t)|\log|S(t)|))$. Therefore, the dynamic incentive method can output results in a polynomial time order.

VI. PERFORMANCE EVALUTION

In this section, we first introduce the comparison method used in the experiment. Then, the experimental setup and evaluation metrics are given to evaluate the performance of our proposed incentive mechanism. Finally, we analyze the experimental results.

A. BASELINE METHODS

To effectively evaluate the performance of IMRAL, we compared the performance of our proposed mechanism IMRAL with the TRAC mechanism proposed in [13] and the IMC-SS mechanism proposed in [18].

1) TRAC [13]

This mechanism is a typical MCS incentive mechanism based on reverse auction model. In the mechanism, the participants bid for multiple sensing tasks according to their location and sensing range, and the platform selects the users with low total bids as the winners.

2) IMC-SS [18]

This incentive mechanism based on MCS is based on SS-Model. This mechanism assumes that each winning provider will complete the task and the platform selects the winner based on the number of bids and tasks reported by the user.

In order to effectively illustrate the effectiveness of the user interaction-based incentive method, we compare the process of recruiting users through UIBIM and recruiting users through the IMRAL mechanism to complete unfinished tasks. And use the task completion rate and platform cost to illustrate the effectiveness of UIBIM.

B. SIMULATION SETTINGS

To verify the validity and feasibility of the IMRAL mechanism, we design a simulation experiment. Table 2 shows the basic parameter settings in the simulation experiment. To evaluate the impact of n, we fix $m = 100$. Similarly, to evaluate the impact of m, we fix $n = 100$. Furthermore, some participants in stage 1 will drop out of the sensing task, here we set the dropping-out possibility $q = 0.2$. We also make the assumption that if a winner exits during sensing, the sensing task is unfinished, here we set the completion ratio $\Delta t_i/t_i$, which represents the actual sensing time of a participant divided by the total sensing that the participant should stay in the system, is uniformly distributed in the range of [0,1]. That is, when a participant quits in stage 1, the sensing task is unfinished, and it is difficult to compute how much of the task the participant has finished, therefore, we consume the task completing ratio is randomly distributed in the range of [0,1].

TABLE 2. Simulation parameter settings of IMRAL.

name	value
user number n	[50-500] with the increment of 50
total number of tasks m	[10-100] with the increment of 10
user bid b_i	uniformly distributed over [5, 10]
cost for each subset c_i	uniformly distributed over [1, 5]
valuation of each task V_i	uniformly distributed over [1, 50]

Then, in order to verify the validity and feasibility of the dynamic incentive method based on double auction, we also design a simulation experiment. The experimental parameters are shown in Table 3. The key factors affecting the effectiveness of the dynamic incentive method include: the number of buyers, the number of sellers, waiting for patience I, and the arrival rate λ. We assume the total auction period $T = 100$. The buyers' bidding and sellers' asking price are uniformly distributed in the range of (0, 5], the arrival probability of a user follows the Poisson distribution. We compare the simulation results under different buyers, sellers, maximum patience, and arrival rate. The default settings of maximum patience and arrival rate are set to 6 and 10 [28].

The experimental scenario of the UIBIM mechanism is that the platform release 100 sensing tasks, and there are 100 users in our MCS system interested in the tasks. First, a user is encouraged to participate in the sensing through the IMRAL mechanism, and then the platform will recruit users to complete unfinished tasks using the IMRAL mechanism

TABLE 3. Simulation parameter settings of UIBIM.

name	value
buyers' bids and sellers' asks	uniformly distributed over (0, 5]
number of buyers α	{10,20,30,40,50}
number of sellers β	{10,20,30,40,50,60,70,80,90,100}
total auction time T	100
maximum patience I	{0, 3 ,6 ,9 , 12, 15, 18, 21, 24, 27, 30}
arrival ratio λ	{1,2,3,4,5,6,7,8,9,10}

and the UIBIM mechanism respectively. When encouraging users to participate in tasks that have not been completed, this paper compared the simulation results of the number of bidding users to {10, 20, 30, 40, 50, 60, 70, 80, 90, 100}. For the UIBIM mechanism, we set the user's arrival rate to 10 and a user's maximum waiting patience to 6.

C. EVALUATION METRICS

First, we compare the IMRAL mechanism with TRAC and IMC-SS in terms of average user utility, platform utility, task coverage, and task completion rate. Secondly, we evaluate the dynamic incentive methods proposed in the second phase of this paper from two aspects: system efficiency and social welfare.

1) AVERAGE USER UTILITY

The average user utility is defined as the ratio between the total utility of all winners and the number of winners, which is defined as: $\frac{\sum_{u_i \in S} p_i - \sum_{u_i \in S} c_i}{|S|}$, where $|S|$ is the number of winners.

2) TASKS COVERAGE RATIO (R)

$R = \frac{cov}{m}$, where cov is the number of tasks covered by winners, and m denotes the total number of tasks.

3) TASK COMPLETION RATE(γ)

The task completion rate γ is defined as the ratio of the number of tasks com completed by all the winners to the total number of tasks m, which is computed as: $\gamma = \frac{com}{m}$.

4) PLATFORM UTILITY

Platform utility is an important assessment indicator for assessing incentives that are budget feasible. It is computed according to (2).

5) SYSTEM EFFICIENCY

The system efficiency μ is defined as $\mu = \frac{|B^W|}{\alpha}$, where $|B^W|$ denotes the number of winning buyers, and α means the total number of buyers.

6) SOCIAL WELFARE

Social welfare is the sum of the utility of all participants. It is computed as $\sum_{u_i^b \in u^b, u_j^s \in u^s} (u(u_i^b) + u(u_j^s)) = \sum_{u_i^b \in B^W, u_j^s \in S^W} (b_i - s_j)$.

D. NUMERICAL RESULTS AND ANALYSIS

1) AVERAGE USER UTILITY

Fig. 5 shows the average user utility of IMRAL, TRAC and IMC-SS, respectively. The impact of m is shown in Fig. 5 (a). For IMRAL, we observe that when the number of tasks is small, the competition between users is stronger, resulting in fewer winners. At this time, the task payment is concentrated on a small number of users, therefore, the average user utility is higher. As the number of task increases, users' choices are more extensive. The above situation will lead to a decrease of user in competition, resulting in an increase in the number of winning users. Since the total value of tasks that can be completed by the users tends to be stable, the average utility of user decreases. From Fig. 5 (b), it shows that, as the number of user increases, the number of tasks that can be completed by a user is improved, and the increase in the total task payment causes the average utility of a user to increase. Comparing IMRAL to TRAC and IMC-SS, the payment of TRAC mechanism and IMC-SS mechanism is only related to the number of bid and task. Due to the cumulative effect of task payment in IMRAL, users can get a relatively higher task compensation, which increases the degree of willingness of users to participate in sensing tasks.

2) TASKS COVERAGE RATIO

Fig. 6 demonstrates the tasks coverage ratio of IMRAL, TRAC and IMC-SS. From Fig.6, it shows that the task

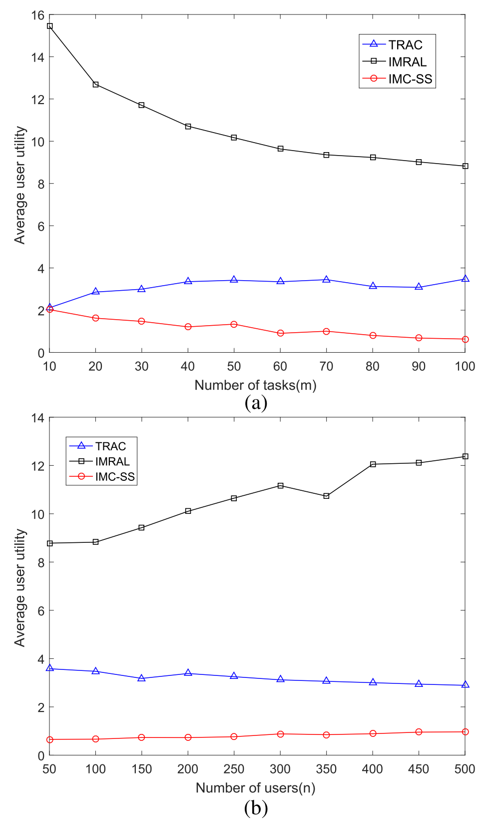

FIGURE 5. The average user utility under different numbers of tasks and users. (a) $n = 100, 10 \leq m \leq 100$. (b) $m = 100, 50 \leq n \leq 500$.

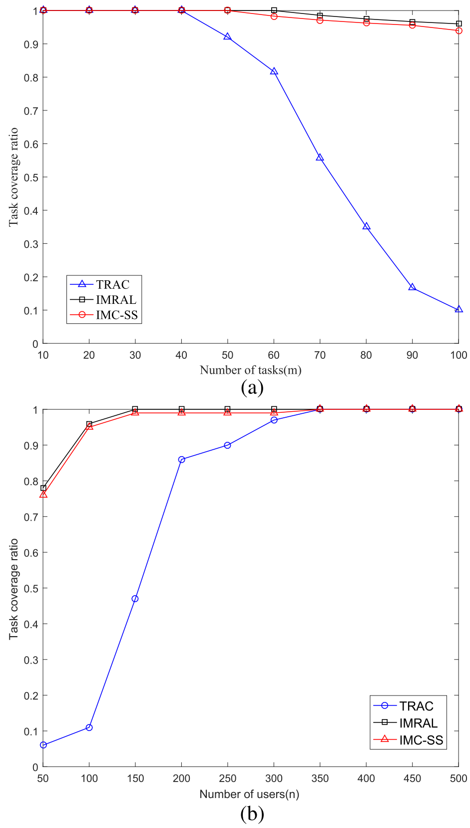

FIGURE 6. The tasks coverage ratio under different numbers of tasks and users. (a) $n = 100$, $10 \le m \le 100$. (b) $m = 100$, $50 \le n \le 500$.

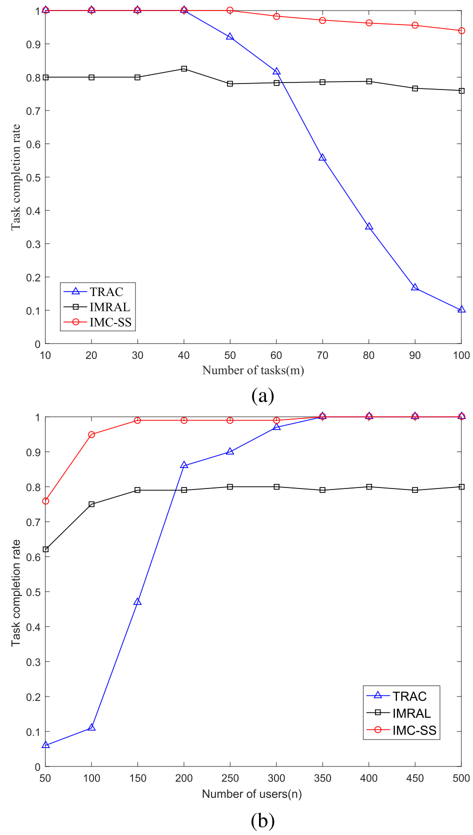

FIGURE 7. The task completion ratio under different numbers of tasks and users. (a) $n = 100$, $10 \le m \le 100$. (b) $m = 100$, $50 \le n \le 500$.

coverage under IMC-SS is slightly lower than the task coverage under IMRAL, and when the number of users is close to or smaller than the number of tasks, the task coverage under TRAC is lower. The main reason is that TRAC chooses users who have low bids greedily and report a large number of tasks during the winner selection stage. In the compensation payment phase, TRAC needs to find a user who includes the user set of the paid user, and completes the payment to the winner. When the number of users is close to or smaller than the number of tasks, it is difficult to find users who meet the requirements to pay the winner.

The above situation causes the user fail to pay, and thus the task coverage is low.

Combined with user utility and task coverage, we can draw the conclusion that users in IMRAL are more motivated than users in TRAC and IMC-SS.

3) TASK COMPLETION RATE

Fig. 7 is a comparison of the sensing task completion rate. Both TRAC and IMC-SS assume that the task coverage is equivalent to task completion, therefore, we also consider the task completion rate is the same as its task coverage. However, IMRAL considers the situation that a sensing task may not be completed due to the user's random drop-off. Fig. 7 (a) shows when the number of users is 100, the task completion rate under three mechanisms increases as the increase of the number of tasks. When the number of tasks is between 10 and 60, the task completion rate under IMRAL is lower than the task completion rate under TRAC and IMC-SS. In Fig. 7(b), when the number of tasks is 100, with the increase of the number of users, the task completion rate under TRAC and IMC-SS approaches 100%. However, since a user may quit during the execution of the task is considered in the IMRAL, there are always tasks that uncompleted.

4) PLATFORM UTILITY

Fig. 8 is a comparison of the utility of the crowd sensing platform. As can be seen from Fig. 8(a), with a certain number of users, as the number of tasks increases, the platform utility under IMRAL and IMC-SS increases. Compared to IMC-SS, the platform utility of IMRAL is lower, and there are two main reasons. First, the exit of a user may cause the task being unfinished, resulting in a lower total value of the completed task. Second, the compensation payment of a user is higher under IMRAL incentive method, so the utility of the platform is lower. Under TRAC, when the number of tasks increases, the platform utility increases first and then decreases. The main reason is that, when the number of users is close to or less than the number of tasks, the task completion rate is low. In Fig. 8(b), the platform utility of the three incentive methods is first increased and then stabilized. The reason is that as

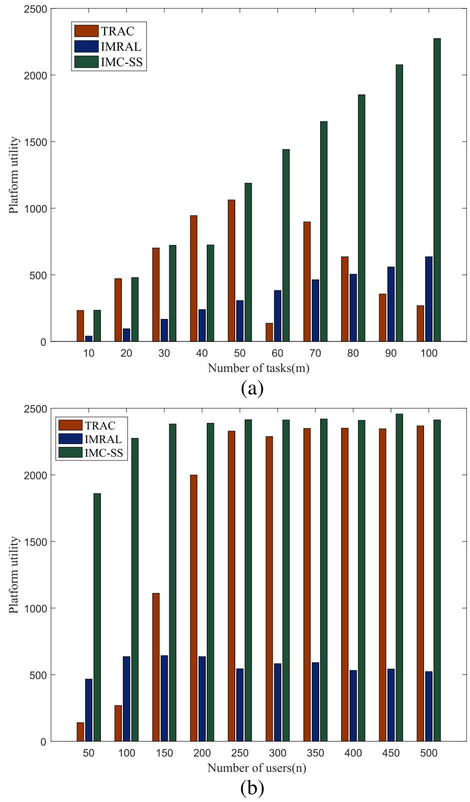

FIGURE 8. The platform utility under different numbers of tasks and users. (a) $n = 100$, $10 \leq m \leq 100$. (b) $m = 100$, $50 \leq n \leq 500$.

the number of users increases, the task completion rate also increases. When the task set is full, the platform utility will not increase.

5) SYSTEM EFFICIENCY

The system efficiency is the ratio of the number of successful buyers to the total number of buyers, reflecting the sensing task completion rate. In Fig. 9, as the number of sellers increases, more task supply lead to more choices. For buyers, more demand can be met, making the system more efficient. Finally, the growth rate of system efficiency slows down and tends to be stable. The reason is that when the number of sellers is fixed, which means that most of the buyers have already completed the transaction, and the additional sellers have contributed little to the system efficiency.

As shown in Fig. 10, when the total number of buyer and seller of the auction is 50, 100 and 150 respectively, the system efficiency increases with the patience of waiting for, because the higher waiting patience will lead to more successful match between the buyers and the sellers.

In Fig. 11, it can be seen that system efficiency increases as the arrival rate increases. The reason is that a higher arrival rate will result in more successful matching of the bid and the asking price.

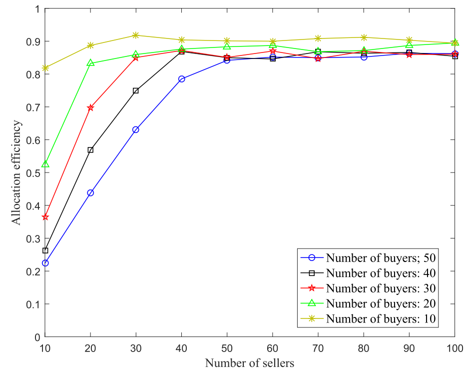

FIGURE 9. Impact of the number of users on system efficiency.

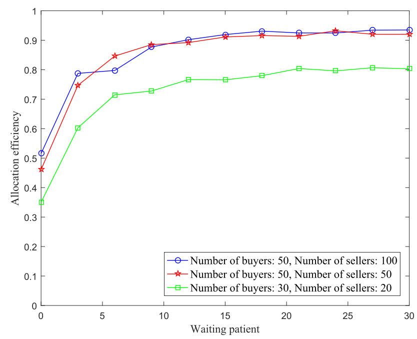

FIGURE 10. Impact of waiting patient on system efficiency.

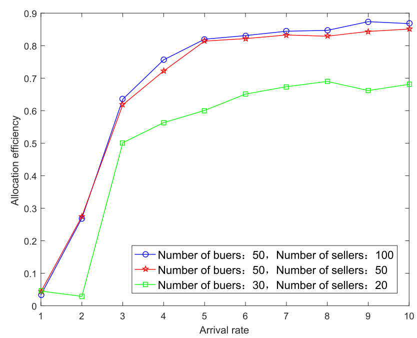

FIGURE 11. Impact of arrival rate of the users on system efficiency.

6) SOCIAL WELFARE

Social welfare reflects economic efficiency. As shown in Fig. 12, an increase in the number of buyers or the number of sellers will lead to an increase in social welfare. The reason is that as the arrival rate increases, more bids will be matched to the asking price.

In Fig. 13, it can be seen that when the total number of buyers and sellers of the auction is 50, 100 and 150 respectively, social welfare increases as the patience of waiting for increases. This is because higher waiting patience will lead to more matching success between bid and asking price.

In Fig. 14, social welfare increases as the arrival rate increases. The reason is that as the arrival rate increases, the probability that the bidding matching an asking-price will increase.

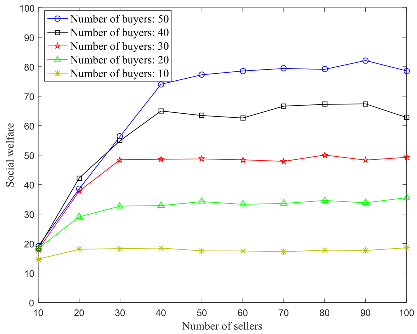

FIGURE 12. Impact of arrival rate of the users on system efficiency.

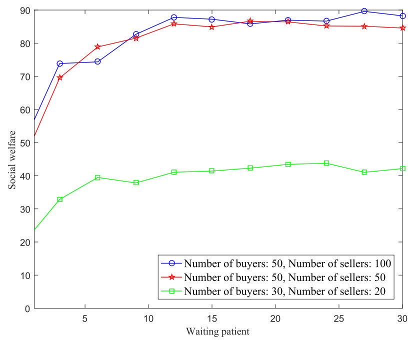

FIGURE 13. Impact of arrival rate of the users on system efficiency.

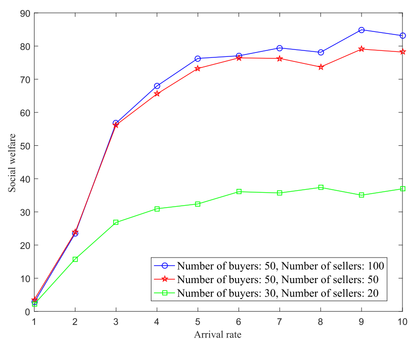

FIGURE 14. Impact of arrival rate of the users on system efficiency.

VII. CONCLUSIONS

In the MCS network, due to the selfishness and randomness of the users' participation in the sensing activities, the enthusiasm of the user to participate and the corresponding task completion rates are usually not high enough. To deal with these problems, this paper proposes a novel incentive mechanism based on a new auction model. Firstly, from the user's perspective, in order to maximize user utility, and considering the randomly exit in the process of a sensing task, this paper proposes an incentive method IMRAL based on reverse auction. In this phase, we proposed a task-centric user selection algorithm with polynomial time complexity. This method can promote user participation and improve the sensing task coverage rate. In addition, we also adopted a method of compensation payment based on the proportion of time sharing, which improves the user's utility while ensuring the truthfulness of the incentive. Secondly, this paper proposes an incentive model based on user interaction. The model improves the sensing task completion rate and social welfare of user's through a dynamic incentive method based on a double auction and a user matching algorithm based on node degree and edge weight. Finally, theoretical and experimental analysis shows that the incentive mechanism of this paper can improve the average user utility and task coverage, and can enable the platform to achieve a higher task completion rate under certain budget constraints. In the future work, we will leverage the machine learning theory, such as clustering algorithm [30] to preprocess the sensing data, and study how to improve the quality (such as data accuracy, security) of the sensing the sensing data. In addition, in order to provide better insights, we will further validate the effectiveness of the proposed incentive mechanism using external crowd sensing dataset.

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